



Segment-based region of interest generation for pedestrian detection in far-infrared images



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HIGHLIGHTS

- We utilize the low-frequency characteristics of FIR images for ROI generation.
- We generate ROIs based on combining image segments instead of using the intensity threshold.
- It generates a small number of ROIs at an acceptable miss rate.
- We introduce miss rate and ROIs per image (ROIPI) to assess the performance of the segment-based ROI generation module.

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ABSTRACT

We present a region of interest (ROI) generation method specialized for nighttime pedestrian detection using far-infrared (FIR) images. Because pedestrians typically appear brighter than background in FIR images, previous research efforts primarily attempted to extract ROIs based on the intensity threshold. However this approach has problems resulting from the intensity variances of pedestrians due to their clothing and, especially in urban scenarios, and other heat sources that emit more heat than the pedestrians. In this paper, we propose a novel ROI generation method that is based on combining image segments instead of using the intensity threshold. In order to minimize dependence on brightness, we utilize the low-frequency characteristics of FIR images. As a result, our proposed method generates a small number of ROIs at an acceptable miss rate and the generated ROIs provide advantages for classification because the pedestrians are satisfactorily arranged within a bounding box. Experiments conducted indicate that our proposed method performs reliably in urban scenarios.

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1. Introduction

Far-infrared (FIR) images, unlike visible spectrum images, capture the heat emitted from objects, so pedestrians typically appear brighter (i.e., they have a relatively higher temperature) than backgrounds. Thus, FIR technology is very suitable for pedestrian detection at night time, when a visible spectrum camera is not usable. Generally, the first step in pedestrian detection is the extraction of ROIs that are highly likely to contain pedestrians. The threshold technique is very useful in detecting warm objects that are likely to be pedestrians, so the majority of earlier research efforts in this area focused on generation of a ROI based on intensity threshold.

Global image threshold is the simplest technique for extracting hotspots. In [1], a simple intensity threshold is chosen experimentally, whereas in [2], the threshold is determined based on the

overall mean of the image, and in [3], the image threshold is set using the mean and maximum intensity values in the current frame. However, these approaches encounter problems when they attempt to determine suitable threshold values. These problems arise from the non-uniform intensities of pedestrians caused by their clothes, multiple neighboring pedestrians, and other objects, such as cars and electric signs being warmer than the pedestrians.

In order to compensate for these limitations, additional steps such as region growing and active contours are used for generating potential candidates. In [4], a seed point is extracted using a high threshold that is near the maximum image intensity, then the seeded region growing method is used to generate candidate images. In [5], an active contour model is used on edge images to extract the boundaries between potential candidates and their backgrounds.

Instead of using each pixel value to extract hotspots, one-dimensional horizontal and vertical image intensity profiles are used to generate candidate bounding boxes. In [6], vertical strips are extracted by the local minima of the horizontal intensity profile generated using brightness threshold, and then vertically

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segmented according to brightness and bodyline estimation. Similarly, in [7], a thresholded horizontal and vertical image intensity profile is used to find intersections between the vertical and horizontal boundaries that define the bright region. Symmetry of intensities, symmetry of vertical edges, and density of vertical edges on a horizontal profile are used to generate candidates in [8].

Although these methods work well, they all require a threshold value to extract bright pixels. Thus, the threshold value still significantly affects the quality of the ROIs.

In addition to pixel brightness, FIR images are characterized by low frequency, a very important characteristic that had not been considered in previous works. Temperature changes are not significant in the same object and FIR is not significantly affected by the texture of an object's surface, so the output of an FIR camera is a low-frequency image containing regions with a similar intensity unlike visible spectrum images. These attributes are well illustrated in Fig. 1. Due to this characteristic, FIR images facilitate to segment an image into regions of similar temperatures.

In this paper, we present a novel ROI generation method for FIR-camera-based pedestrian detection systems. Image segmentation is used for extracting segments of pedestrian candidates, and ROIs are generated by combining the segments with commonly used geometric constraints. We evaluate the performance of the proposed ROI generation module itself, and its pedestrian detection results on FIR image sequences using the single frame evaluation method.

2. The proposed ROI generation method

ROI generation is the process of finding regions that are highly likely to contain a pedestrian. In FIR images, pedestrians appear brighter than backgrounds because FIR cameras capture the heat emitted from objects. Hence, most of the previous approaches set their start point as the intensity threshold to utilize this characteristic instead of using the sliding windows technique, which is frequently used in visible-spectrum-camera-based pedestrian detection.

As mentioned in [4], the FIR signature of pedestrians can be distorted because of their clothing. As a result, pedestrians may appear as several regions of similar intensities rather than a single region of uniform intensity. This results in difficulties when extracting pedestrian segments using intensity threshold, so we do not consider bright pixels but regions of similar intensities instead. In our work, instead of beginning with an intensity threshold, we start the module using image segmentation.

2.1. Image segmentation

To generate an ROI we do not seek hot spots based on an intensity threshold; instead, we use segments composed of pixels with

similar intensities. Although a pedestrian image does not have uniform intensity, as expected in FIR images, it is divided into several regions that have a similar intensity. The idea underlying our approach stems from this characteristic. Because of this characteristic, intensity threshold based methods experience difficulty finding suitable thresholds: a threshold that is too high causes the pedestrian candidate to be split into several blobs, whereas one that is too low distorts the pedestrian candidate by dispersing the background pixels. To overcome these problems, previous works utilized post processing techniques such as region growing and active contours to find the boundary between pedestrians and their backgrounds. We solve these problems in somewhat of a reverse order. To obtain the boundaries between pedestrians and their backgrounds, instead of spreading from the seed point that is extracted considering the intensity threshold, our approach starts with image segmentation, because FIR images facilitate image segmentation and enables the extraction of foreground heat source objects from their backgrounds. By applying image segmentation to an FIR image, although the pedestrian image is split into several segments, they are differentiated from their background. Thus, through the proper combination of those segments, ROIs can be extracted effectively. Fig. 2 shows several image segmentation results.

We use a mean shift segmentation algorithm to extract segments because the results produced using this algorithm are readily controlled using a few parameters and this method also provides reliable performance. The mean shift algorithm is a mode seeking algorithm that was made popular for image segmentation by Comaniciu and Meer [9]. To generate results, users only need to set the parameters for the spatial and range resolutions (h_s, h_r), which control the size and number of segments, while options such as the minimum size of a segment (M) can be used to eliminate small segments. Suitable parameters can be determined experimentally to extract pedestrian segments. Clustering of pixels is performed as the parameters h_s in the spatial domain and h_r in the range domain; thus a smaller value for each parameter tends to generate segments with smaller sizes. Fig. 3 shows the results of parameter variations. As shown in the figure, the range parameter h_r controls the number of regions: because the neighboring pixels are grouped together in the range domains (i.e. gray-levels in our case), as it becomes larger, the number of segments is reduced, and the boundary between pedestrians and their background may become blurred. Hence, pedestrians may be merged into the background. A similar effect occurs when the spatial parameter increase: because distant pixels are grouped together in the spatial domain, as spatial parameter h_s becomes larger, the boundaries between object and background tend to become blurred. To determine the parameters, we evaluated ROI generation performance versus parameter variations using miss rate



Fig. 1. Sample images of pedestrians at a crosswalk. (a) Visible spectrum image (640 × 480). (b) Far-infrared image (320 × 240).

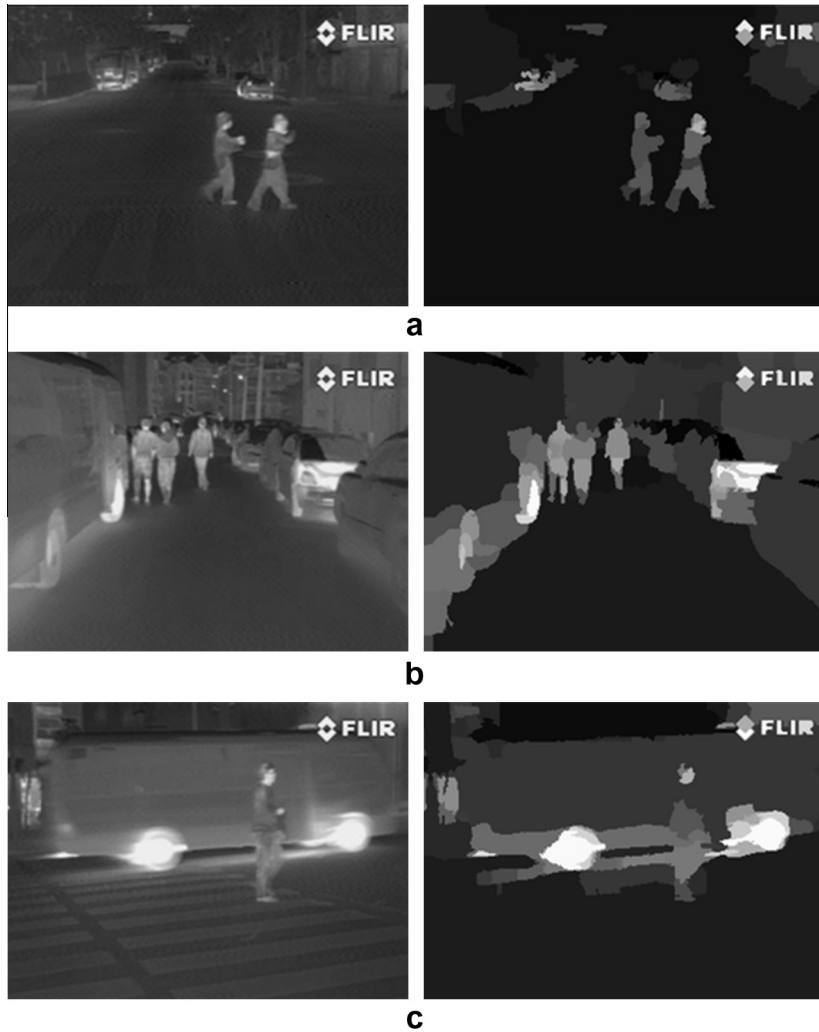


Fig. 2. Images resulting from image segmentation. (a–c) Left column shows the FIR camera input image and the right column shows the result of image segmentation (segmented with parameters $(h_s, h_r, M) = (9, 5, 30)$).

and ROIs per image. The details of the measurements used are given in Section 3.1. In accordance with the results of the evaluations, we set parameters (h_s, h_r, M) to $(9, 5, 30)$, as shown in Fig. 3b. The output of mean shift segmentation is a labeled image of segments. These segments are used to extract ROIs by constraint combinations.

2.2. Segment-based ROI generation

As shown in the image segmentation results, pedestrians are usually split into several segments rather than appearing as a single segment because of differences in heat emission from parts of their bodies, their clothes, bags, and other such accessories. Hence, we consider as candidates not only single segments but also combinations of pairs of segments. With this kind of combination, we look for a pair of segments comprising head and leg to generate a bounding box by connecting the two segments.

A similar segmentation-based candidate selection method is utilized in [10], for visible spectrum images. The method utilized generates candidates using only single segments in a segmented image of multiple scales, not pairs of segments, in order to find unbroken objects by scale variations. However, the method is time consuming and it is also difficult to acquire single unbroken

candidates because edges are not strong in FIR images. As the targets of our applications are pedestrians on roads, the combinations can be restricted by combining vertically ordered segments. This makes the combination solution very simple.

Since tens of segments of FIR images exist as a result of image segmentation, it is not rational to consider all the possible combinations of pairs of segments for ROI generation. To reduce the number of possible combinations, only relatively bright segments are considered for combination as those having a higher probability of being a part of a pedestrian. Thus, only segments that are brighter than the background segment (which is selected according to the largest one occupying the lowermost rows due to the fact that the ground is merged into a single segment, as the ground region has uniform intensity) are considered for combination. Fig. 4a shows an example of the extraction of segments that is brighter than the background segment.

The horizontal overlap ratio (defined as the ratio of the intersection and the union) between segments is the rule used to combine pairs of segments because pedestrians are perpendicular to the ground and pedestrian segments are also separated horizontally (for example, into head, body, and legs). The horizontal overlap ratio (s_o) is calculated between segments (seg_a, seg_b) with their horizontal length ($length_h$) as:

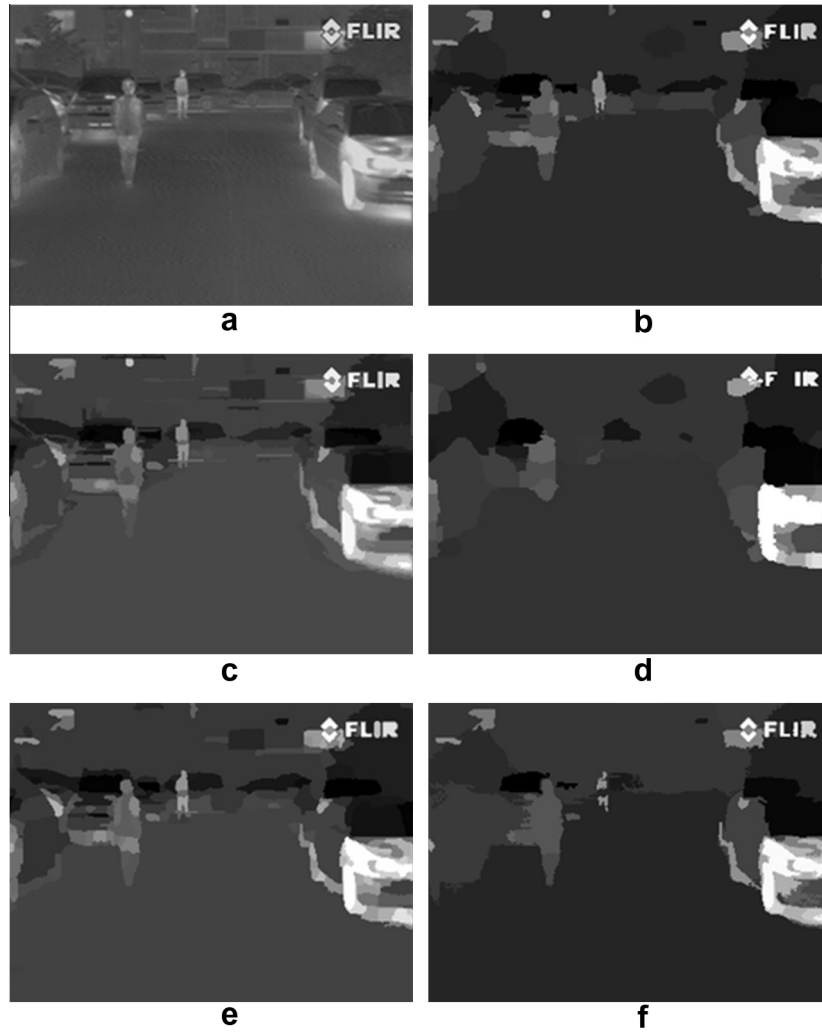


Fig. 3. Images resulting from spatial and range resolution parameter variations. (a) Input image. (b) Segmented image with $(h_s, h_r, M) = (9, 5, 30)$ which was used for our detection system. (c) $(h_s, h_r, M) = (9, 1, 30)$. (d) $(h_s, h_r, M) = (9, 20, 30)$. (e) $(h_s, h_r, M) = (3, 5, 30)$. (f) $(h_s, h_r, M) = (20, 5, 30)$.

$$S_o = \frac{\text{length}_h(\text{seg}_a \cap \text{seg}_b)}{\text{length}_h(\text{seg}_a \cup \text{seg}_b)} \quad (1)$$

In our experiments, pairs of segments in which the horizontal overlap exceeded 30% (which was determined experimentally) were assigned to the candidate and its bounding box (defined as a rectangle with the left-uppermost coordinate and the right-lowermost coordinate determined by the coordinates of the pairs of segments) is generated as illustrated in Fig. 4b, with segments of the pedestrian. Fig. 4c shows the candidate images in full.

At this point, geometrical constraints are generally used to filter out impractical candidates such as candidates that are too far away and candidates that are too big or too small for that distance. This procedure can reduce the number of ROIs needing classification and can also reduce false negatives. The constraints that we used were flat world assumption, ground-plane-based objects, and the height of the pedestrians. Fig. 5 illustrates the constraints that were placed on the candidates. In our work, only pedestrians with a height of 1–2 m within a distance of 50 m were considered targets.

In the cases where the constraints were met, the width of the bounding box was changed to fix an aspect ratio (defined as the ratio of the width to the height) of 0.5. The final result of ROI generation is shown in Fig. 6. As shown in the figure, a small number of ROIs containing pedestrians were successfully extracted.

3. Results and discussion

In this section, we introduce miss rate and ROIs per image (ROI-PI) to assess the performance of the segment-based ROI generation module. We then evaluate pedestrian detection performance by extracting features using histograms of local intensity differences (HLID) from the ROIs and classify using linear support vector machine (SVM). Test images amounting to 6573 frames were taken from a moving vehicle in an urban area at nighttime.

3.1. Evaluation of the segment-based ROI generation method

We evaluated our proposed ROI generation method using 1905 of the 6573 images, excluding the images used for classifier training. The image sequences included 1480 pedestrians with an image size (height in pixels) ranging from 33 to 179 pixels that were manually labeled with the ground truth by bounding boxes, the aspect ratio of which were the same as the bounding boxes of the ROI. We followed the single frame evaluation method used by Dollar et al. [11]. Evaluations were performed between the generated bounding box of the ROI (BB_{ROI}) and the ground truth bounding box (BB_{GT}). The matching condition between a BB_{ROI} and a BB_{GT} is defined as the area of overlap (a_o):

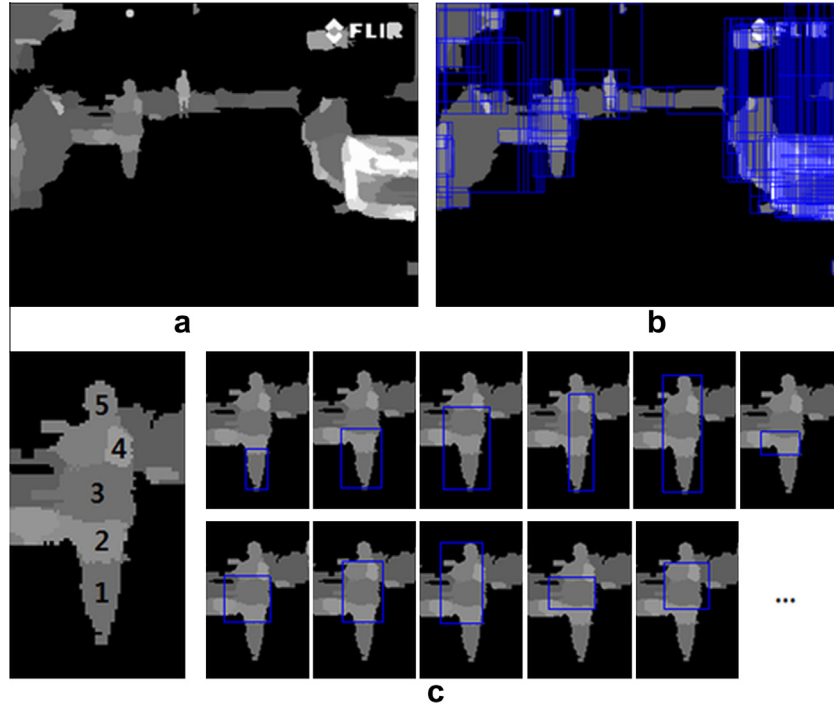


Fig. 4. Procedure used for segment-based candidate generation. (a) Bright segment extraction for combination (all the non-black segments are considered prime segments for combination). (b) Examples of candidate generation. Left: pedestrians are split into five segments that are numbered for illustration. Right: single segments are the candidate itself and a pair of segments can be candidates if they satisfy the horizontal overlap ratio. (From upper-left, candidates are generated in segments of {1}, {1,2}, {1,3}, {1,4}, {1,5}, {2}, {2,3}, etc.). (c) The 498 candidates generated from the overlapped pairs of segments in the current frame.

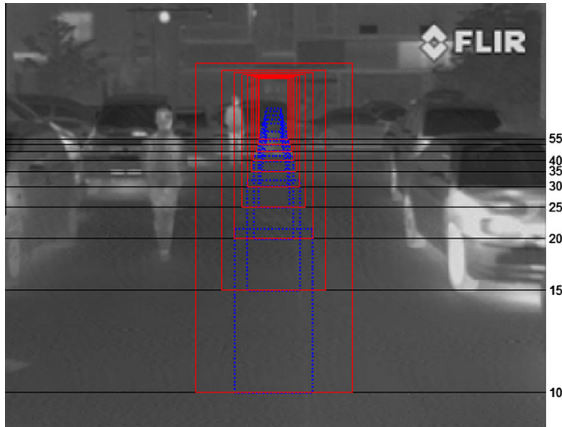


Fig. 5. Geometric constraints for extracting practical candidates (each red box has a height of 2 m and each blue box has a height of 1 m at each distance, numbers on the right side indicate the distance in meters). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

$$a_0 = \frac{\text{area}(BB_{ROI} \cap BB_{GT})}{\text{area}(BB_{ROI} \cup BB_{GT})} > 0.5 \quad (2)$$

The condition states that their area of overlap must exceed 50% (we followed this parameter as in [11]). Under this condition, an unmatched BB_{GT} is counted as a false negative whereas an unmatched BB_{ROI} is counted as a false positive.

The main objective of ROI generation is to accurately capture the ROIs that contain pedestrians without missing any candidates using a small number of ROIs as possible. Hence, we computed miss rate and ROIs per image (ROIPI) to determine the efficiency as well as the accuracy of the ROI generation module. The results are illustrated in Fig. 7 as mean shift parameters variations. To

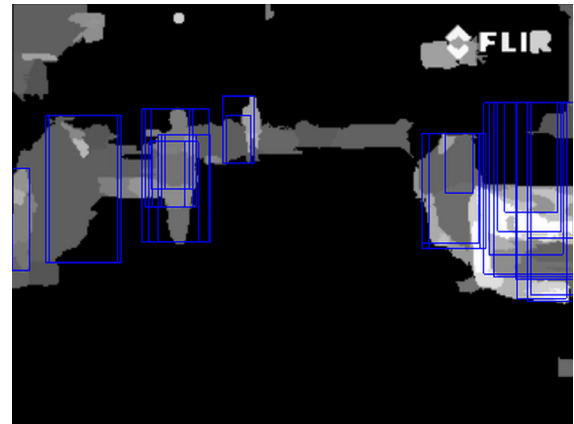


Fig. 6. Final result of ROI generation (27 ROIs generated).

show the correlation between the ROI performance of the result and detection performance, we tested the detection performance of representative cases among the variations as shown in Table 1. The results are shown in Fig. 8. The details of the detection methods experiments are described in Section 3.2. From the results, we can conclude that, as we expected, not only miss rate but also ROIPI have to remain small in order to achieve better detection performance, because the miss rate of ROI generation module affects the miss rate of the overall system and a large ROIPI increases the number of false positives.

It is difficult to compare our results with those of other researchers because this method of evaluating ROI generation methods has not been done before. The conventional evaluation method used by researchers is to assess the performance using final detection results combined with the classification module. However, this method of evaluating the ROI generation module is

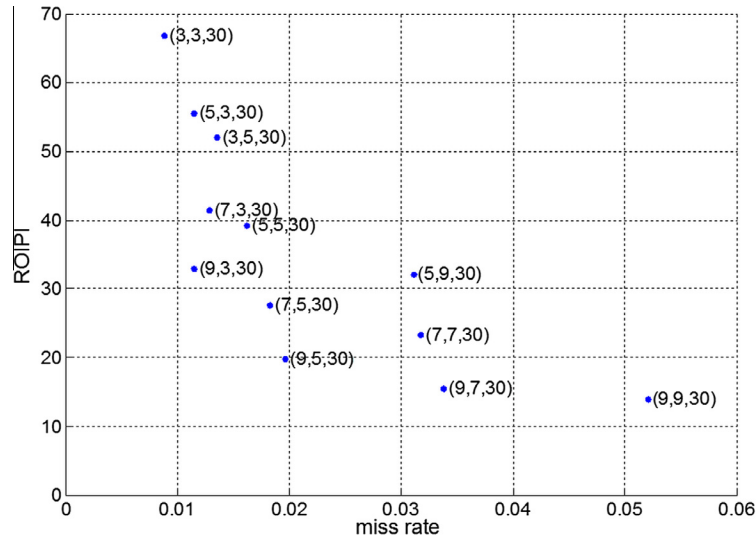


Fig. 7. Performance measures using miss rate versus ROIPI of our proposed ROI generation method as mean shift parameter (h_s, h_r, M) variations.

Table 1

Performance measures of our proposed ROI generation method as mean shift parameter variations.

(h_s, h_r, M)	ROIPI	Miss rate (%)
(3, 3, 30)	66.84	0.88
(9, 3, 30)	32.97	1.15
(9, 5, 30)	19.92	1.95
(9, 7, 30)	15.61	3.38
(9, 9, 30)	13.99	5.20

Table 2

Performance measures of the intensity threshold-based sliding window technique as sliding resolution variations.

Longitudinal resol. (m)	Lateral resol. (m)	ROIPI	Miss rate (%)
1.5	0.3	136.4	1.8
1.0	0.2	310.9	0.47
0.5	0.1	1248.2	0.13

confusing because pedestrian detection results are affected not only by the ROI generation module but also by the choice of features, classifiers, and techniques used to merge multiple detections. Using the sliding window technique, however, it may be possible to show that our results are meaningful because it is a well-known ROI generation method. To generate ROIs using the sliding window technique, we adapted the geometric constraints to reduce the number of ROIs. Further, we adopted the intensity threshold to each window to retain bright regions that are highly

Table 3

Test parameters for HLID.

Parameter	Value
Sample size	24×48 pixels
Cell size	6×6 pixels
No. of directions	8-bin
Radius	2
Block size	2×2 cell
Overlap	0.5 block
Normalization method	2-norm

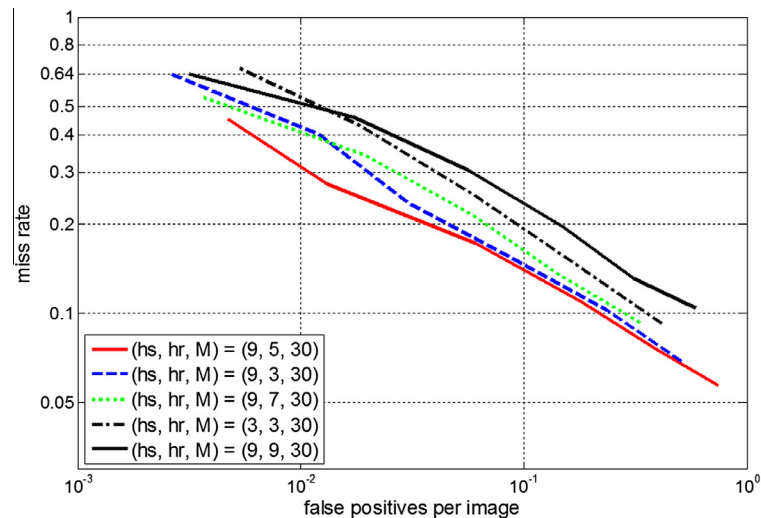


Fig. 8. Detection performance comparison results as mean shift parameter variations (the legend gives the order of performance by the miss rate at 10^{-1} FPPI).

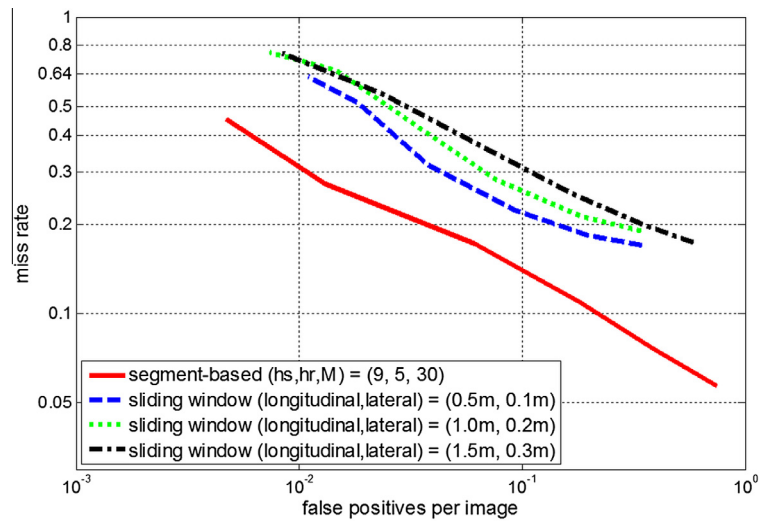


Fig. 9. Segment-based ROI generation and intensity threshold-based sliding window technique pedestrian detection evaluation results (the legend gives the order of performance by the miss rate at 10^{-1} FPPI).

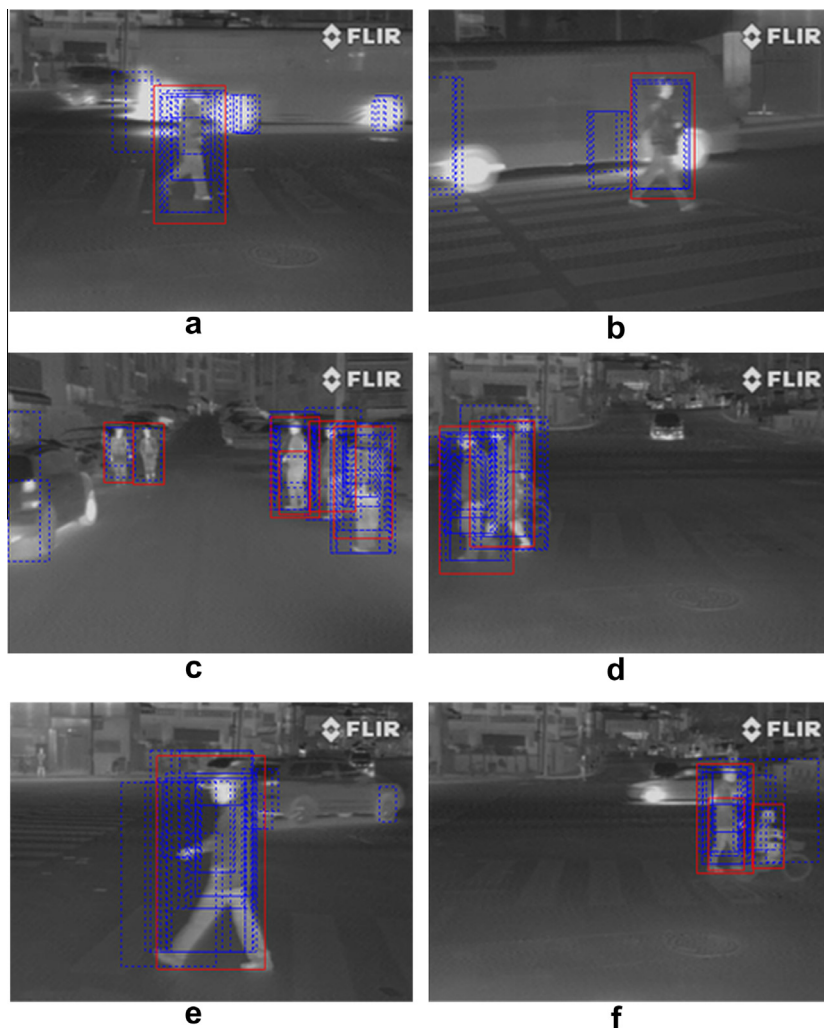


Fig. 10. Detection examples using representative scenarios (the red boxes indicate the detection results while the blue dotted boxes indicate the generated ROIs). (a and b) Pedestrian with hot spots. (c and d) Multiple pedestrians close to each other. (e) A pedestrian that is very near (f) Small pedestrians are also included. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

likely to contain a pedestrian, which is the start point set by most researchers in previous approaches. In this way, we indirectly compared our method to the intensity threshold-based technique. The threshold value was set optimally for test image sequences and approximately 90% of the ROIs were filtered out. The results are shown in Table 2 with sliding resolution variations. If the ROIPI is not considered, the miss rate appears to be better than that of our method in cases where the sliding ratio is dense. However, the quality of the ROIs is worse than those obtained using our method. The bounding boxes obtained using the sliding window technique do not include well-arranged candidates because they are obtained with a fixed size and in a fixed position. This makes it difficult to generate the right answers from a classifier that is trained using properly arranged samples. To compensate for this problem, more dense sliding resolutions or bounding boxes of various heights can be used. However, these types of solutions will significantly increase the number of ROI. Further, the large number of ROIs increases the number of false positives and degrades the detection performance.

While the results of our proposed method vary according to the candidates, the candidates are suitably arranged in the bounding box due to the boundaries between the objects, and the backgrounds are well defined as segments by image segmentation. This characteristic increases the detection performance of the classifier.

In the best-case scenario, $(h_s, h_r, M) = (9, 5, 30)$, the results from our proposed method generated only approximately 20 ROIs per frame with a reasonable miss rate. False negatives occurred mainly when the pedestrian segments merged into overlapping objects that emitted heat with a similar intensity, such as vehicles. This is a common limitation of FIR-based detection systems and it needs to be rectified in future work.

3.2. Evaluation of the pedestrian detection performance of the proposed ROI generation method

To evaluate the pedestrian detection performance of our proposed ROI generation method, we extracted the HLID feature

[12], a modified version of histograms of oriented gradients (HOG) [13] used to specify FIR images, from the ROIs. HLID expresses a sample image on the basis of its local shape and appearance using histograms of local intensity differences. The parameters used to extract the features are shown in Table 3. The features were classified using a linear SVM.

After classification, the pair wise max (PM) suppression technique [14], which discards every pair detected having a low confidence, was used to merge multiple detections of a pedestrian. The matching condition between the detection and the ground truth was the same as that used for the ROI evaluation in Eq. (2) except for the fact that bounding box of detected (BB_{DT}) was used instead of BB_{ROI} . The performance of the pedestrian detection is demonstrated using the detection error tradeoff (DET) curve, which plots the miss rate against the false positives per image (FPPI) rate on a log–log scale.

We compared our result to that of the intensity threshold-based sliding window technique described in Section 3.1. The result is shown in Fig. 9. Even though the sliding window technique has a lower miss rate than our method, our method still outperformed it. If the arrangement of candidates in the captured ROI is not taken into consideration, these results are to be expected as the sliding window method generates many more ROIs than our method. However, as we indicated, it is important that both the miss rate and the ROIPI remain small. Because test sequences were captured in urban areas, in addition to pedestrians a lot of other heat sources exist. This causes many scattered hot pixels in thresholded images. Hence, a large number of ROIs are generated in the threshold-based sliding window technique due to those hot regions. However, our proposed method still generated only a small number of ROIs under these conditions—which accounts for the differences in detection performance results.

In addition, the sliding window technique results show that well aligned ROIs are also important for better performance because a dense sliding ratio results in better performance even though many more ROIs are generated. Therefore, the effects of arrangement need to be considered in future work.

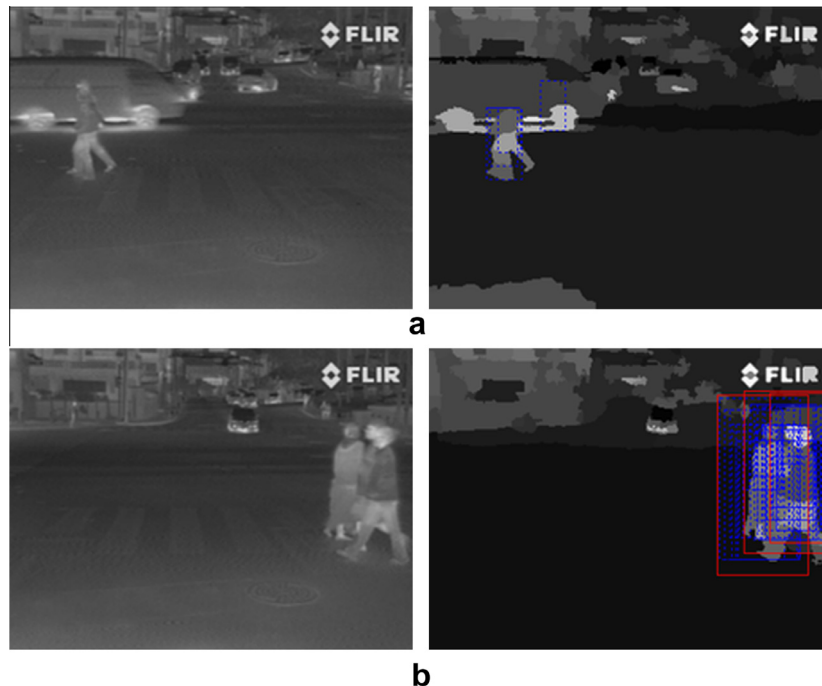


Fig. 11. Limitations of the FIR-based system. (a) Detection failure because of similar intensity as other objects. (b) Unstable detections due to pedestrians overlapping each other to a large extent.

Representative results illustrating the advantages of the segment-based ROI generation method and the limitations of FIR-based pedestrian detection are shown in Figs. 10 and 11. Our proposed method was not affected by the presence of objects that were warmer than the pedestrians because they were separated into different segments (Figs. 10a and b). This is in direct contrast to the intensity threshold techniques, which are severely affected by these hot spots. When multiple pedestrians walked close to each other in the street scenarios, the pedestrians were detected separately (Figs. 10c and d). In cases where pedestrians were near, they were split into more segments than those that were in the medium or far distance, and were detected successfully (Fig. 10e). Further, small pedestrians over 1 m in height were detected successfully, as shown in Fig. 10f. However, when the intensity of the pedestrian was similar to other overlapping objects or when pedestrians overlapped each other to a large extent, it was still difficult to detect them. In these cases, we expect that additional algorithms such as component-based classification [15] or tracking will prove helpful in improving the detection performance (Fig. 11).

4. Conclusion

We proposed a novel ROI generation method for pedestrian classification based on FIR images. Experimental results show that the proposed method has reliable performance in the urban scenario without relying on the intensity threshold. This novel approach utilizes the low-frequency characteristic, which is a salient characteristic of FIR images. Further, our proposed method generates a small number of ROIs at an acceptable miss rate and the generated ROIs provide advantages for classification because the pedestrians are satisfactorily arranged within a bounding box. Further, the small number of ROIs is advantageous for real time implementation of the systems.

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